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MODELING UPPER CITARUM WATERSHED HYDROLOGY USING SWAT+ AND GSMAP PRECIPITATION DATA

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ABSTRACT: Hydrological modeling is a vital tool for understanding the complexities of the hydrological cycle. The Soil and Water Assessment Tool Plus (SWAT+), a semi-distributed hydrological model, simulates processes across various spatial and temporal scales. With advancements in hydrological modeling, integrating satellite data has become essential to address input data variability and improve analysis accuracy. This study evaluates the performance of satellite data as a primary input for SWAT+ in hydrological modeling. The model was validated against observed streamflow data, with performance assessed using Nash-Sutcliffe Efficiency (NSE), Percent Bias (PBIAS), and flow duration curves (FDC). Despite the model successfully capturing general seasonal patterns of wet and dry streamflow at a monthly scale, metric results showed suboptimal NSE and PBIAS values, reflecting significant discrepancies between simulated and observed data. This study highlights the potential of satellite data to mitigate data challenges in hydrological modeling while emphasizing the need to refine input data quality and parameterization to improve performance. The findings provide a foundation for further integrating remote sensing data into SWAT+ applications.

Keywords: Hydrological modelling, SWAT+, Satellite data, Model performance

1. INTRODUCTION

Hydrological modeling is an essential tool in managing water resources, as it enhances understanding by simulating the complex processes of the hydrological cycle [1]. Hydrological models can evaluate the interactions between precipitation, surface runoff, soil moisture, and groundwater flow by capturing the dynamics of the processes [2]. The Upper Citarum Watershed, located in Indonesia, is a vital water source for millions of people and plays a central role in the region’s economy [3,4]. This area faces urbanization, deforestation, and climate change challenges, leading to water management problems [5]. Climate change also significantly impacts hydrological processes, altering precipitation, evaporation, and streamflow patterns [6]. Those changes challenge water supply sustainability and increase the risks of droughts and floods [7]. Predicting future streamflow is critical for effective water resource planning and management [8].

The Soil and Water Assessment Tool Plus (SWAT+) is a powerful tool for addressing these challenges [9]. With its advanced capabilities to simulate hydrological processes under various scenarios for watershed-scale [9,10]. As the new version of SWAT, the SWAT+ model is a continuous-time, semi-distributed, process-based river basin model specifically developed to assess the impacts of various management practices on water, sediment, and agricultural chemical yields. This model simulates streamflow and pollutant transport across a range of spatial and temporal scales, considering environmental conditions, land management strategies, and scenarios related to land use and climate change [11]. The development of SWAT+ has provided an enhancement of spatial flexibility, improvement in the simulation of landscape processes, and management practices that facilitate more accurate scenario analyses [12]. Its application is becoming increasingly common across various disciplines, particularly for hydrological modeling [13], flood modeling [14], and analyzing rainfall patterns [15].

Despite its advantages, SWAT+ faces challenges in accurately integrating input data variability, particularly at the Upper Citarum Watershed. The development of hydrological modeling aims to create advanced tools that improve the accuracy and reliability of analyses. However, another significant modeling challenge is integrating input data variability. Satellite data emerges as a valuable resource capable of bridging these gaps. Satellite data is widely recognized for providing data globally, such as land surface data [16], meteorological and weather data [17], topographic and elevation data [18], and atmospheric data [19]. However, integrating satellite data introduces complexities, including resolution mismatches and discrepancies with ground-based measurement.

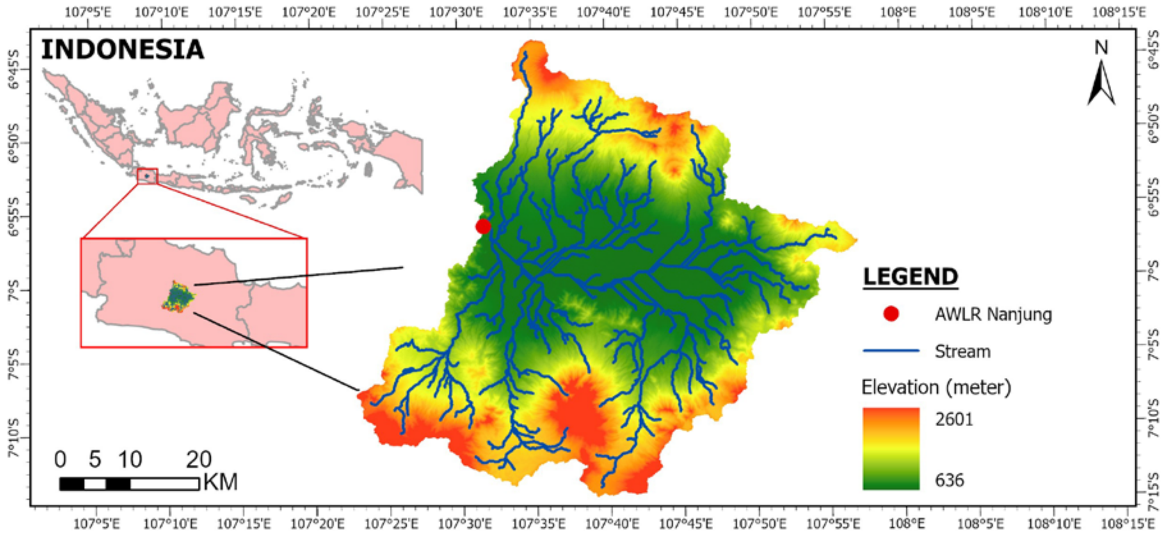

Fig. 1 Location map of the study area. The colors represent the elevation, ranging from 636 to 2601 meters above sea level (m asl)

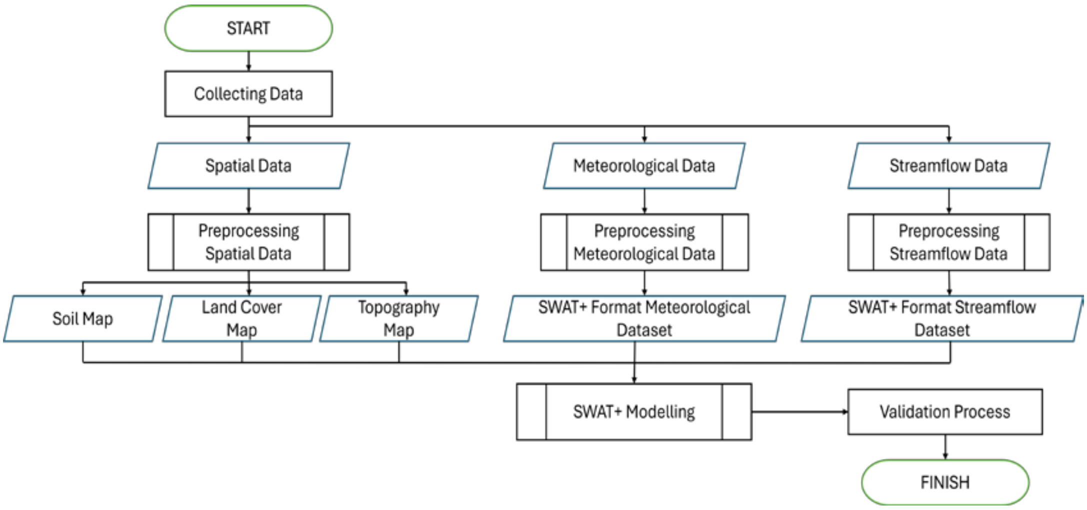

Fig. 2 Methodology flowchart

The study applies the SWAT+ model to the Upper Citarum Watershed, using key inputs such as land cover, topography, soil type, rainfall, streamflow, and meteorology data to simulate hydrological processes and evaluate the model's performance. This research aims to enhance the SWAT+ applications by addressing data integration and model efficiency challenges and providing more accurate streamflow predictions and valuable insights for water resource management in the Upper Citarum and similar watersheds.

This study is structured into five sections. Section 2 emphasizes the significance of the research. Section 3 provides an overview of the study area and details the methodology, including data processing and performance evaluation. The results are presented and discussed in Section 4 with an emphasis on the model's performance and capabilities. Lastly, section 5 offers a conclusion by summarizing the findings, discussing the significance, and suggesting directions for future research.

2. RESEARCH SIGNIFICANCE

This study focuses on SWAT+ hydrological modeling, employing satellite data as the primary input in the Upper Citarum Watershed. By focusing exclusively on satellite data, the research establishes a basis for further investigation into using remote sensing data in hydrological modeling. Moreover, the study provides valuable insights into the performance and applicability of this approach in hydrological research.

3. MATERIALS AND METHODS

3.1 The Study Area

The study area is the Upper Citarum Watershed in the West Java province of Indonesia. This watershed encompasses the upper stretches of the Citarum River, covering an area of 1,828 km^2 [20] (Fig. 1). The study area's topography is characterized by its remarkable diversity, ranging from altitudes of approximately 636 m in the lower plains to over 2601 m in the mountain area. The landscape is predominantly mountainous, interspersed with a relatively flat central basin. The watershed includes several districts, specifically Bandung and Cimahi cities, as well as the West Bandung, Bandung, and Sumedang regencies. The region has diverse land covers, predominantly urban and agricultural fields, forested areas, and shrubland [21]. Fig. 1 illustrates the location map of the study area, and Fig. 2 shows the methodology flow chart for this study.

3.2 SWAT+ Model

SWAT+ has introduced the Landscape Position Unit (LSU), a new spatial unit positioned between the subbasin and the Hydrological Response Unit (HRU). Within the SWAT+ framework, the watershed is first divided into several subbasins and subdivided into LSUs and HRUs. HRUs represent distinct areas within a subbasin that share similar characteristics, including land use, soil type, and slope. In contrast, LSUs are characterized based on their geographic location within the subbasin, representing specific areas such as uplands, floodplains, or other landscape features. The water balance equation for the SWAT+ models hydrologic cycle follows the Eq. (1). [22].

$$SW_{t,i} = SW_{0i} + \sum_{i=1}^{t} (R_{day,i} - Q_{surf,i} - E_a - W_{seep,i} - Q_{gw,i} \quad (1)$$

3.3 Data Collection and Preparation

SWAT+ requires three types of data: spatial, meteorological, and streamflow. Spatial data such as topography, land cover, and soil type data are employed to characterize the features of the watershed. Meteorological data, such as rainfall, humidity, wind speed, solar radiation, and temperature, is used as input for modeling hydrological processes. Lastly, streamflow data is utilized to evaluate the model's accuracy and reliability in simulating streamflow within the watershed.

3.3.1 Topography data

The topography data for the Upper Citarum Watershed was sourced from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM). This dataset has a spatial resolution of 30 meters [23]. This globally sourced DEM was developed by the National Aeronautics and Space Administration (NASA) in collaboration with the National Geospatial-Intelligence Agency (NGA). The dataset is freely accessible and can be downloaded from the United States Geological Survey's (USGS) Earth Explorer (https://earthexplorer.usgs.gov/).

Topography data is fundamental in SWAT+ as it characterizes the physical attributes of the watershed. This data is used to delineate watersheds and define subbasin boundaries, map stream networks, and calculate flow direction and accumulation. A topography map of the Upper Citarum Watershed is shown on Fig. 1.

3.3.2 Land cover data

In this study, the land cover map was derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) dataset [24]. Specifically, the MODIS Land Cover Type MCD12Q1 dataset, known for its annual global land cover classifications, was utilized [25]. This dataset provides a spatial resolution of 500x500 meters and employs the LC_Type1 layer, which categorizes the land cover into 17 categories according to the International Geosphere-Biosphere Programme (IGBP) classification system [26].

Land cover data is essential in SWAT+ for defining the spatial distribution of vegetation, agricultural areas, urban areas, and various land cover within the watershed. This data forms the foundation for characterizing the Hydrologic Response Units (HRUs): areas with uniform land use, soil, and slope attributes. These characteristics directly impact the simulation of hydrological processes, including surface runoff, evapotranspiration, and infiltration [27,28].

SWAT+ utilizes land cover data in two complementary formats: raster and text. The raster format, typically provided as GeoTIFF files, illustrates the spatial distribution of various land cover types across the study area, with each pixel assigned a code linked to a lookup table for detailed categorizing. The text files, in CSV format (.csv), offer additional parameterization for each land cover type, including crucial attributes such as leaf area index, root depth, and growth characteristics. A land cover map of the Upper Citarum Watershed is shown in Fig. 3.

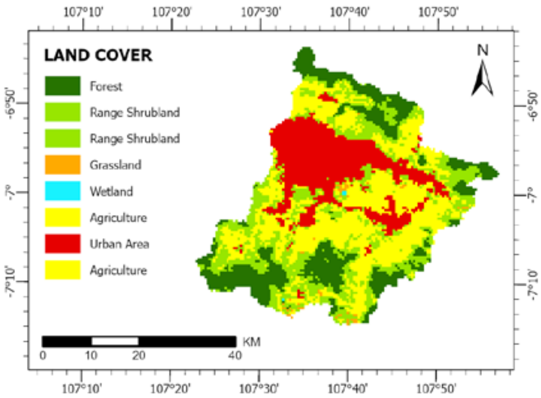

Fig. 3 Land cover map of the Upper Citarum Watershed

3.3.3 Soil type data

For this study, the soil type map was obtained from the Food and Agriculture Organization's (FAO) Digital Soil Map of the World (DSMW) [29]. This global database is available in both raster and vector formats. The data is subdivided into ten regions at a 1:5,000,000 scale and encompasses approximately 4,930 mapping units. Each unit is classified at a basic soil level, providing a robust foundation for hydrological modeling.

Understanding soil properties is pivotal in hydrological analysis using SWAT+, as soil characteristics are a foundation for determining water movement, storage, and availability within a watershed [22]. Soil-type data defines fundamental physical and hydraulic properties, such as bulk density, available water capacity, and hydraulic conductivity**.** These properties are crucial for simulating core hydrological processes, including evapotranspiration, percolation, and surface runoff. By capturing the spatial variability of soil characteristics, SWAT+ enables delineating spatial variability in soil characteristics, which is essential for modeling water flow and nutrient transport.

In the SWAT+ framework, soil data must be provided in raster and text formats, similar to land cover data requirements. The raster format (tiff files) visually represents the spatial distribution of soil types across the study area, with each pixel coded to correspond to a specific soil classification. The text file (.csv) provides comprehensive parameters for each soil type, including bulk density, available water capacity, hydraulic conductivity, and soil texture, ensuring detailed representation in the model. A soil map distribution of the Upper Citarum Watershed is illustrated in Fig. 4.

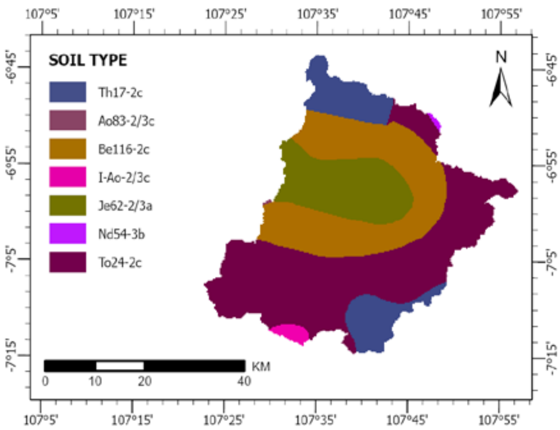

Fig. 4 Soil type map of the Upper Citarum Watershed

3.3.4 Rainfall data

In hydrological modeling, rainfall serves as the primary input for forcing data. This data drives the simulation of various processes within the hydrological cycle, including surface runoff, infiltration, evapotranspiration, and groundwater recharge in a watershed. The quality and resolution of rainfall data are paramount, as they directly influence the model's accuracy in predicting streamflow and accessing water resource availability [30].

Rainfall data utilized in the SWAT+ model typically consists of daily data derived from local meteorological stations or global datasets. In this study, the rainfall data was obtained from the Global Satellite Mapping of Precipitation *(*GSMaP) dataset, developed by the Japan Aerospace Exploration Agency (JAXA) [31]. The GSMaP dataset provides global satellite-based precipitation data with a high temporal resolution of intervals and a spatial resolution of 0.1° x 0.1°. For this analysis, the hourly data from 2014 to 2022 were aggregated to derive daily precipitation values, ensuring compatibility with the SWAT+ model requirements.

3.3.5 Meteorological data

SWAT+ requires meteorology data such as relative humidity (%), solar radiation (MJ/m²), maximum and minimum temperatures (°C), and wind speed (m/s). These data are essential for calculating the evapotranspiration within the study area. Meteorological data can be obtained from local weather stations or global datasets.

This study obtained meteorological from NASA's Prediction of Worldwide Energy Resources (POWER) database [32]. POWER provides extensive global solar and meteorological datasets for various applications, including renewable energy, building energy efficiency, and agriculture. The dataset offers daily temporal data with a spatial resolution of 0.5° x 0.5°. Data from 2014 to 2022 were extracted and processed for this analysis to meet the SWAT+ requirement.

3.3.6 Streamflow data

Streamflow data are essential for validating the accuracy of hydrological simulations. The process involves comparing model predictions with observed values from streamflow data. The dataset covers the period from 2014 to 2022, providing a reliable foundation for evaluating the model's performance. This study's daily streamflow data was sourced from the Automatic Water Level Recorder (AWLR) at Nanjung station, managed by Balai Besar Wilayah Sungai (BBWS) Citarum. BBWS is a regional authority under the Indonesian Ministry of Public Works and Housing responsible for managing river basins, water resources, and infrastructure within its jurisdiction. The Nanjung gauge recorded a minimum streamflow of 7.92 m³/s during the dry season and a maximum streamflow of 453 m³/s during the wet season.

3.4 Model Performance

Time series plots with two statistical methods and the flow duration curve (FDC) were used to evaluate the SWAT+ model performance based on the streamflow data. The two statistical criteria for evaluating the goodness of the streamflow model's predictions are the Nash–Sutcliffe efficiency (NSE) and the percent bias (PBIAS).

NSE is a metric used to assess the predictive accuracy of hydrological models by comparing observed and simulated data [33]. NSE values range from $-\infty$ to 1, where an NSE of 1 signifies perfect model performance. An NSE of 0 indicates that the simulation predictions are no more accurate than the average of the observed data. In contrast, negative NSE values indicate that the mean of the observed data serves as a better predictor than the simulation itself.

The PBIAS (Eq. (2)) metric assessed the average tendency of simulated data to be larger or smaller than their observed data [34]. A PBIAS optimal value of zero signifies that there is no bias present. Positive values imply that there is an underestimation, while negative values imply an overestimation in the simulated data.

$$PBIAS = 100\ x \left(\frac{\sum_{i=1}^{n} (Q_o - Q_m)}{\sum_{i}^{n} Q_o} \right) \tag{2}$$

Where n, Qo, and Qm, are described the number of sampling points, streamflow observed and simulated, respectively.

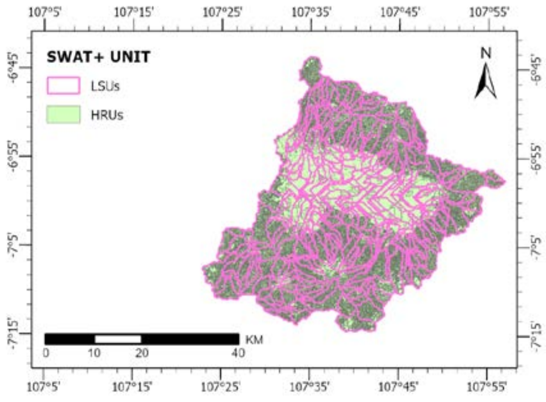

Fig. 5 Model setup result in the Upper Citarum Watershed

4. RESULT AND DISCUSSION

4.1 SWAT+ Model Setup

The SWAT+ model was configured using a DEM to delineate the Upper Citarum Watershed, identifying 26 subbasins. The HRUs were defined by integrating spatial data on land use, soil types, and slope categories. This comprehensive process yielded 4,711 HRUs constructed within the watershed shown in Fig. 5, representing the watershed heterogeneity.

4.2 Model Performance

The model was simulated from 2014 to 2022, divided into a 2-year warm-up period followed by a 7-year validation period. The warm-up phase was implemented to allow the model to stabilize its internal state by reducing the influence of uncertain initial conditions and ensuring consistency before the validation phase. During the validation phase, the model's outputs were compared against observed streamflow data to evaluate its ability to replicate real-world hydrological behavior.

Despite this structured approach, the model exhibited suboptimal performance, particularly on a daily scale, with an NSE of -4.95 and a PBIAS of -34.21. The NSE and PBIAS results indicate significant discrepancies between simulated and observed data. The NSE value below zero indicates that the mean of the observed flow data would have been a better predictor than the model itself. The negative PBIAS emphasized the model systematically overestimating streamflow during wet periods, leading to inflated peak flows. Conversely, during dry periods, the model underestimated the streamflow, indicating its limitations in simulating low-flow conditions (Fig. 6). These results showed the difficulty of the model in capturing the variability and extremes of the hydrological cycle.

The model demonstrated moderate improvement on a monthly scale, yielding an NSE of -1.20 and a PBIAS of 28.11. While these values still indicate suboptimal performance, the model captured the general seasonal patterns of streamflow, as shown in Fig. 7. For example, the model successfully identified the transition between wet and dry seasons, albeit with systemic biases.

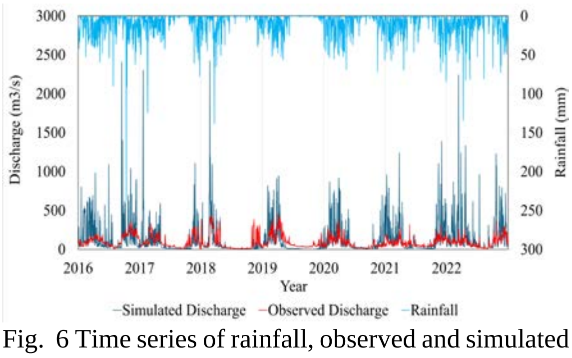

Fig. 6 Time series of rainfall, observed and simulated streamflow on a daily scale

The overestimation of water availability during wet seasons was particularly pronounced, while it was notably lower during dry seasons. These results are potentially due to an overresponse to rainfall or an insufficient representation of infiltration and storage processes. They suggested that the model's representation of soil processes, surface-subsurface interaction, or runoff processes may require refinement [35,36] (Fig. 7).

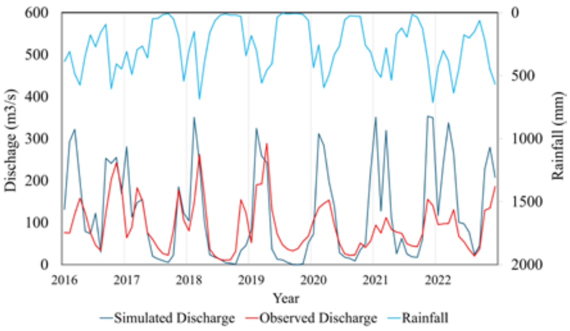

Fig. 7 Time series of rainfall, observed and simulated streamflow data on a monthly scale

Further insight into the model's performance was obtained through the FDC in Fig. 8, which evaluates the distribution of streamflow across the probability thresholds [37]. Based on Fig. 8, the model exhibited limitations in accurately representing both low and high-flow dynamics. The low flow events that occurred above 50% probability were underestimated by 60%, suggesting deficiencies in the representation of baseflow dynamics and groundwater contribution to streamflow. Low-flow events are predominantly controlled by the groundwater contribution and release mechanism, which depends on parameters such as baseflow alpha, baseflow contribution, and aquifer storage [38,39]. Refining the value of these parameters through calibration can enhance the accuracy of the simulation of low-flow events.

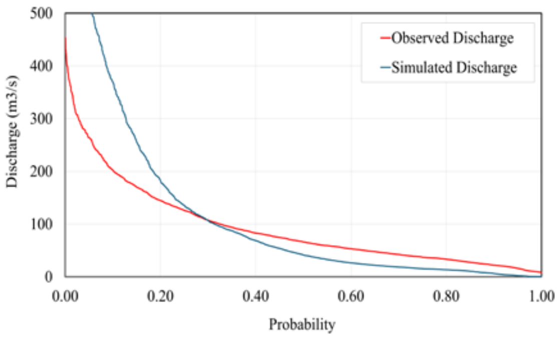

Fig. 8 Comparison the flow duration curve of observed and simulated streamflow

The model over-estimation in high flow events, events below 50% probability, by 28% indicates a bias in its response to extreme rainfall events. This discrepancy suggests potential inaccuracies in the model's runoff and routing process. The result may derive from the model parameter values, which allocate an excessive amount of precipitation to direct runoff while scarcely distributing it for baseflow or catchment storage. This aligns with the tendency to underestimate low-flow events, which may be attributed to surface and runoff processes. By adjusting the parameter values related to the surface and runoff processes, it is possible to reduce the high-flow event while enhancing low-flow results [40].

Furthermore, the study underscores the model the inherent uncertainties in predicting extreme hydrological events. The observed deviations in peak flow data and low flow indicate that, while GSMaP data effectively reflects general trends, its accuracy diminishes during both high-intensity and low-intensity rainfall events. These findings align with previous studies, which indicated that GSMaP data tends to underestimate precipitation intensity in high-elevation areas while slightly overestimating it in low-elevation regions, highlighting the influence of topography on data accuracy [41]. Given the varying elevation within the Upper Citarum Watershed, it could compromise the precision of rainfall measurements

5. CONCLUSION

This study assessed the performance of the SWAT+ hydrological model in the Upper Citarum Watershed when utilizing remote sensing data as a primary input. The result demonstrates that the SWAT+ model exhibited suboptimal performance, indicating significant limitations in accurately simulating hydrological processes under default parameters. The model's accuracy was evaluated using metrics such as NSE and PBIAS. While the model captured the seasonal trends in streamflow, it struggled with precise predictions, showing an NSE of -4,95 and a PBIAS of -34.21 on a daily scale. The model performance indicates overestimation during wet periods and underestimation during dry periods. These results highlight the challenges of streamflow modeling in regions with limited data but also demonstrate the potential of satellite data in hydrology modeling. It is also crucial to meticulously review the input data utilized in the SWAT+ model. Even minor discrepancies in the input data can significantly impact the reliability of the model outputs. However, the model captured the general seasonal patterns of streamflow and identified the transition between wet and dry seasons on a monthly scale.

Despite the limitation, the study highlights the potential of satellite data in hydrological modeling. The global spatial and temporal coverage provided by satellite data offers a basis for model development. Parameter optimization and bias correction for satellite-derived precipitation and evapotranspiration are important to improving model performance.

Future research should focus on implementing robust calibration processes, such as manual adjustment and automatic parameterization offered by SWAT+, to refine the model parameters. Additionally, incorporating bias correction for satellite precipitation estimates and hybrid approaches that combine satellite and ground-based data, should be explored to improve model reliability and applicability.

6. ACKNOWLEDGMENTS

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